

Parametric Approaches for Refractivity-From-Clutter Inversion

Peter Gerstoft

Marine Physical Laboratory, Scripps Institution of Oceanography

La Jolla, CA 92093-0238

phone: (858) 534-7768 fax: (858) 534-7641 email: gerstoft@ucsd.edu

Award Number: N00014-05-1-0369

<http://www-mpl.ucsd.edu/people/gerstoft>

LONG-TERM GOALS

The long term goal of this project is to develop inversion approaches that enable the estimation of refractivity profiles and the associated uncertainty. Furthermore, we will develop methods for mapping the refractivity parameters and their associated uncertainty into propagation.

OBJECTIVES

The objective of this proposal is the development of parametric approaches for the inversion of radar clutter data to estimate atmospheric refractivity over land and sea. Refractivity inversion algorithms using land clutter with and without radar phase will be developed. Over the sea we will further develop our approaches to carry out estimation in time and space of the refractivity.

APPROACH

We have considerable experience in carrying out refractivity estimation from ocean clutter data [Gerstoft et al., 2003a, 2003b, Gerstoft et al., 2004; Rogers et al., 2004]. Little has been done to indicate the quality of the solution for each parameter, either with the variance of the parameter estimate or preferably the complete *a posteriori* distribution. We have already done much work on this in an ocean acoustic context, but this has not been explored in our refractivity from clutter (RFC) processing to date. This will entail developing likelihood formulations and importance sampling algorithms. This inversion approach will show the information content in the data, the importance of each parameter, and the quality of the inversions. Another related topic is that in RFC inversions, we commonly invert each data block independently. When these inversions are close in time (i.e., successive looks in time at the same azimuth) or space (i.e. adjacent azimuths), it should be beneficial to use the results of the previous inversion as a starting condition for the next inversion. A natural framework for this is a Bayesian approach where the posterior of the last inversion becomes the prior for the current inversion. For this investigation, the Bayesian approach will be implemented using a Metropolis-Hastings Gibbs sampler.

WORK COMPLETED

A method for estimation of the radio refractivity from radar clutter using Markov Chain Monte Carlo (MCMC) samplers with a likelihood-based Bayesian inversion formulation has been introduced. This

Report Documentation Page				Form Approved OMB No. 0704-0188	
Public reporting burden for the collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.					
1. REPORT DATE 30 SEP 2006		2. REPORT TYPE		3. DATES COVERED 00-00-2006 to 00-00-2006	
4. TITLE AND SUBTITLE Parametric Approaches for Refractivity-From-Clutter Inversion				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S)				5d. PROJECT NUMBER	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) University of California, San Diego, Scripps Institution of Oceanography, 9500 Gilman Drive, La Jolla, CA, 92093				8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)				10. SPONSOR/MONITOR'S ACRONYM(S)	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION/AVAILABILITY STATEMENT Approved for public release; distribution unlimited					
13. SUPPLEMENTARY NOTES					
14. ABSTRACT					
15. SUBJECT TERMS					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT Same as Report (SAR)	18. NUMBER OF PAGES 9	19a. NAME OF RESPONSIBLE PERSON
a. REPORT unclassified	b. ABSTRACT unclassified	c. THIS PAGE unclassified			

approach enables us to obtain full n -dimensional posterior probability distributions for the unknown parameters as well as the maximum likelihood solution itself [Yardim 05a, 05b, 06].

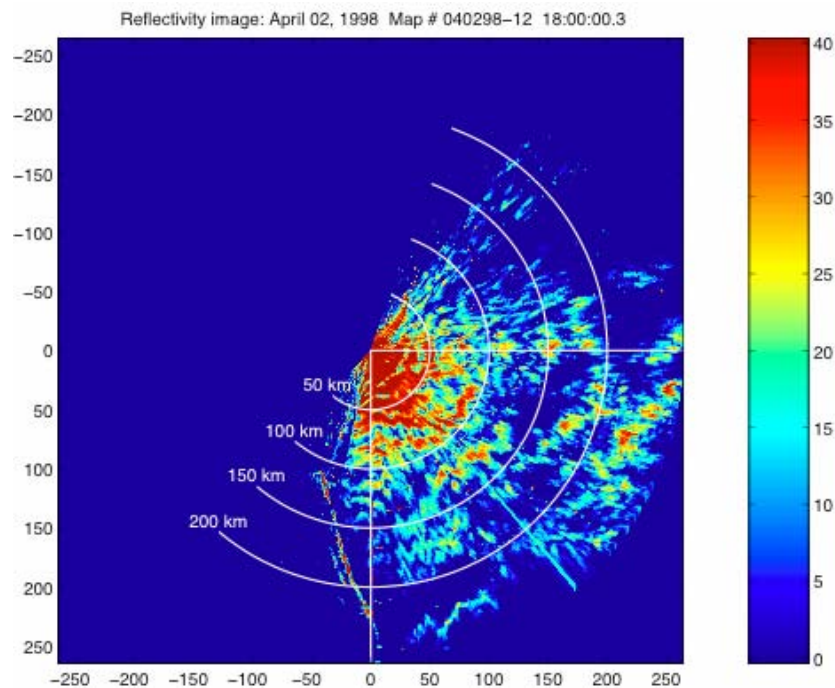


Figure 1 Clutter map from Space Range Radar (SPANDAR) at Wallops Island, VA.

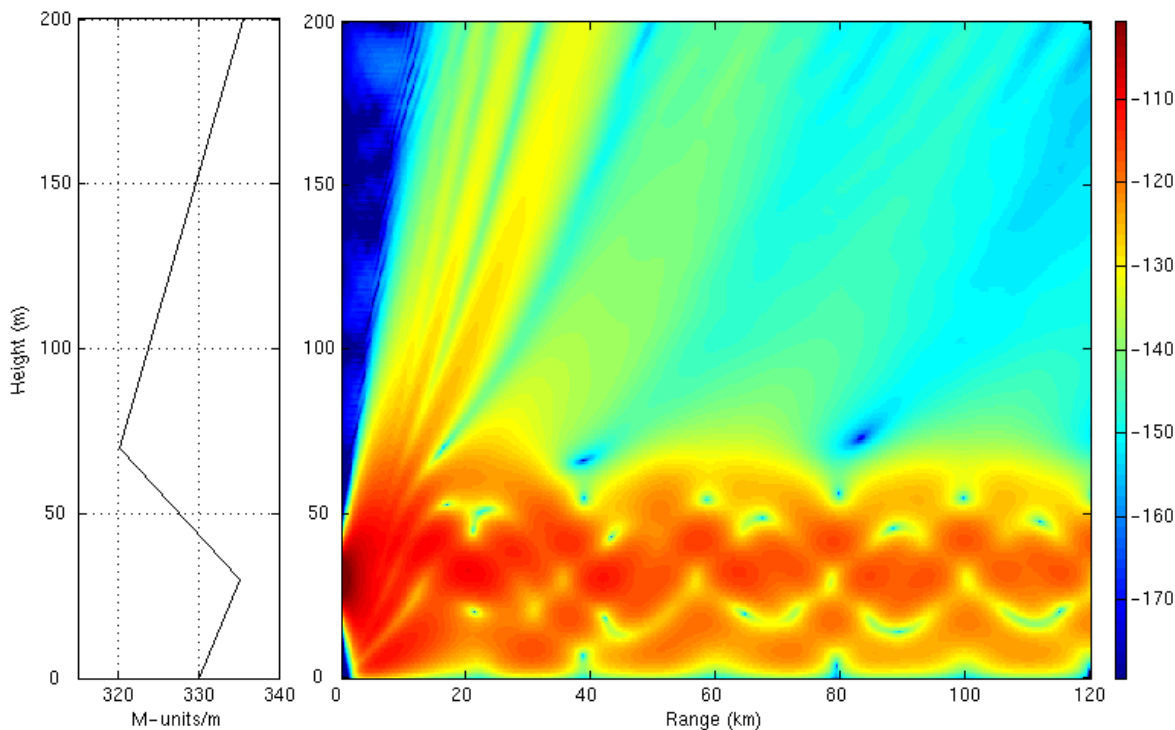


Figure 2 Tri--linear M-profile and its corresponding coverage diagram.

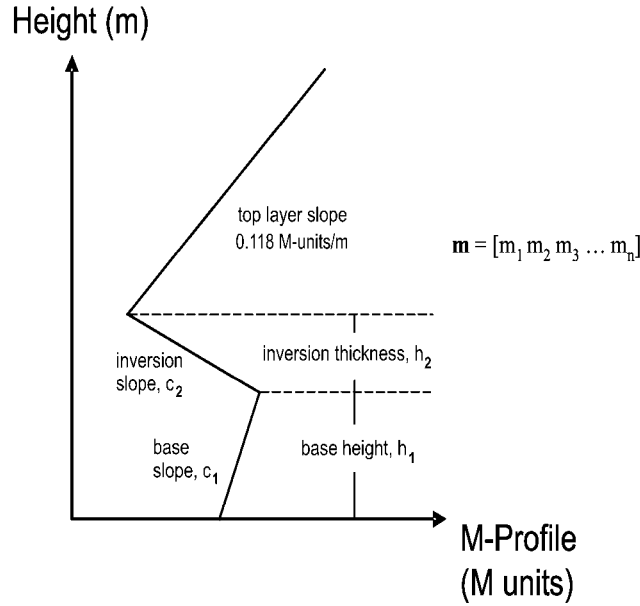


Figure 3 The 4-parameter tri-linear M-profile model used in this work.

RESULTS

An accurate knowledge of radio refractivity is essential in many radar and propagation applications. Especially at low altitudes, radio refractivity can vary considerably with both height and range, heavily affecting the propagation characteristics. One important example is the formation of an electromagnetic duct. A signal sent from a surface or low altitude source, such as a ship or low-flying object, can be totally trapped in the duct. This will result in multiple reflections from the surface and they will appear as clutter rings in the radar PPI screen (Fig. 1). In such cases, a standard atmospheric assumption with a slope of modified refractivity of 0.118 M-units/m may not give reliable predictions for a radar system operating in such an environment.

Ducting is a phenomenon that is encountered mostly in sea-borne applications due to the abrupt changes in the vertical temperature and humidity profiles just above large water masses, which may result in an sharp decrease in the modified refractivity (M-profile) with increasing altitude. This will, in turn, cause the electromagnetic signal to bend downward, effectively trapping the signal within the duct. It is frequently encountered in many regions of the world such as the Persian Gulf, the Mediterranean and California. In many cases, a simple tri-linear M-profile is used to describe this variation. The coverage diagram of a trapped signal in such an environment is given in Fig. 2.

As detailed in the paper [Yardim at 2006] we have developed a likelihood based Markov Chain Monte Carlo (MCMC) sampler, which we have compared to a classical genetic algorithm and an exhaustive grid sampling. The exhaustive grid sampling is only possible for search spaces of small dimensions.

In previous work, genetic algorithms (GA) and Markov chain Monte Carlo (MCMC) samplers were used to calculate the atmospheric refractivity from returned radar clutter. Although GA is fast and estimates the maximum a posteriori (MAP) solution well, it poorly calculates the multi-dimensional

integrals required to obtain means, variances and underlying posterior probability distribution functions (PPD) of the estimated parameters. Accurate distributions and integral calculations can be obtained using MCMC samplers, such as the Metropolis-Hastings (M-H) and Gibbs sampling (GS) algorithms. Their drawbacks are that they require a large number of samples relative to optimization techniques such as GA and become impractical with increasing number of unknowns.

A hybrid GA-MCMC method based on the nearest neighborhood algorithm (NA) is implemented. It is classified as an improved GA method which improves integral calculation accuracy through hybridization with a MCMC sampler. Since it is mainly GA, it requires fewer forward samples than a MCMC, enabling inversion of atmospheric models with a larger number of unknowns.

MCMC samplers are much faster than exhaustive search, but still need much more forward model runs than GA. Therefore, it will be very desirable to have a GA-MCMC hybrid method that combines the speed of GA with the accuracy of MCMC. Due to its inherent properties, Gibbs sampler (GS) is the best MCMC algorithm for such a hybrid method. Hence, the hybrid method will be called the GA-GS hybrid. The method consists of three distinct sections:

1. **GA:** Run a classical GA, minimizing the misfit, and save all the populations and the misfit values of all generations.
2. **Voronoi Cells and Approximate PPD:** Using the GA samples and their likelihood values construct Voronoi cells (see next section) around each GA point, assigning the likelihood of each GA point to all points inside its own Voronoi cell. This will result in an approximate PPD.
3. **GS:** Run a fast GS on the approximate PPD instead of the real one. Since the conditional densities and the likelihood values required to run GS is known for the approximate PPD, no forward model is needed.

This process simply is a discretization of the original PPD. It will convert the true analog PPD into a digital one through an A/D converter. The only difference is that, this A/D converter is n -dimensional, and hence, discrete levels are tiny n -dimensional hypercubes. These hypercubes are called Voronoi cells. The shapes and sizes of these cells are determined by the GA sample set. There is only one GA sample in each cell and there does not exist any other GA sample, which is closer to any point inside this hypercube. Hence, for any boundary point between any two adjacent cells, the distances of that point to the two closest GA samples are same. Due to this feature, it is also called the nearest neighborhood (NN) method [Sambridge, 1998]. In each cell, the likelihood value is assumed to be constant with a value of its GA sample. Therefore, the likelihood of any point anywhere in the entire search space is known and there is no need for any further forward model runs. A very fast GS, without any forward modeling, is used to sample this approximate PPD. The accuracy of the results depends mostly on the quality of the approximate PPD, which means that, GA should gather enough samples from all over the n -dimensional search space to allow the NN algorithm to construct a good enough n -dimensional mesh, hence a good enough approximate PPD.

The method has been carefully validated in Yardim et al [2007]. Here we present inversion results of clutter return from the 1998 Wallops experiment as also described in Yardim et al [2007]. We represent the environment using a range dependent refractivity profile as given in Fig 5. The environmental posterior density is given in Fig. 6(a). Since the full PPD is 16-D, only 1-D (diagonal

plots) and 2-D (upper diagonal) marginal densities calculated are given. Some of the parameters such as m_{10} , m_{12} and m_{14} have a highly non-Gaussian marginals, while others such as m_2 , m_3 and m_9 have Gaussian-like features. The highly skewed 1-D marginals given for m_{10} and m_{14} are encountered frequently with the refractivity slope pdf's. The reason is that the slope very rarely exceeds values such as 0.3--0.4 M-units/m and usually is concentrated around values such as 0.118 M-units/m (standard atmosphere) and 0.13 M-units/m. This creates a sharp peak for the positive end of the spectrum since the negative slope values can be in excess of the -2 M-units/m, usually with a quickly decreasing probability. The result is a pdf structure similar to the ones obtained here. In fact, Gerstoft et al [2004] uses such a pdf as prior density to do importance sampling.

The environmental statistics can be projected into statistics for user parameters (see Sec II of Yardim et al [2007]). One typical parameter of interest to an end-user is the propagation factor F . The results in Fig. 7 are obtained from the parameter PPD in Fig. 6. It shows the PPD for F at ranges (a) 18, (b) 40, and (c) 60 km. Contour plots show the PPD of F for height values between 0-200 m, with the MAP solution (dashed white). Horizontal lines represent the three altitudes analyzed in detail in the small plots shown next to the color plots. Comparison of plots at the same range and different altitudes reveals some important aspects of RFC.

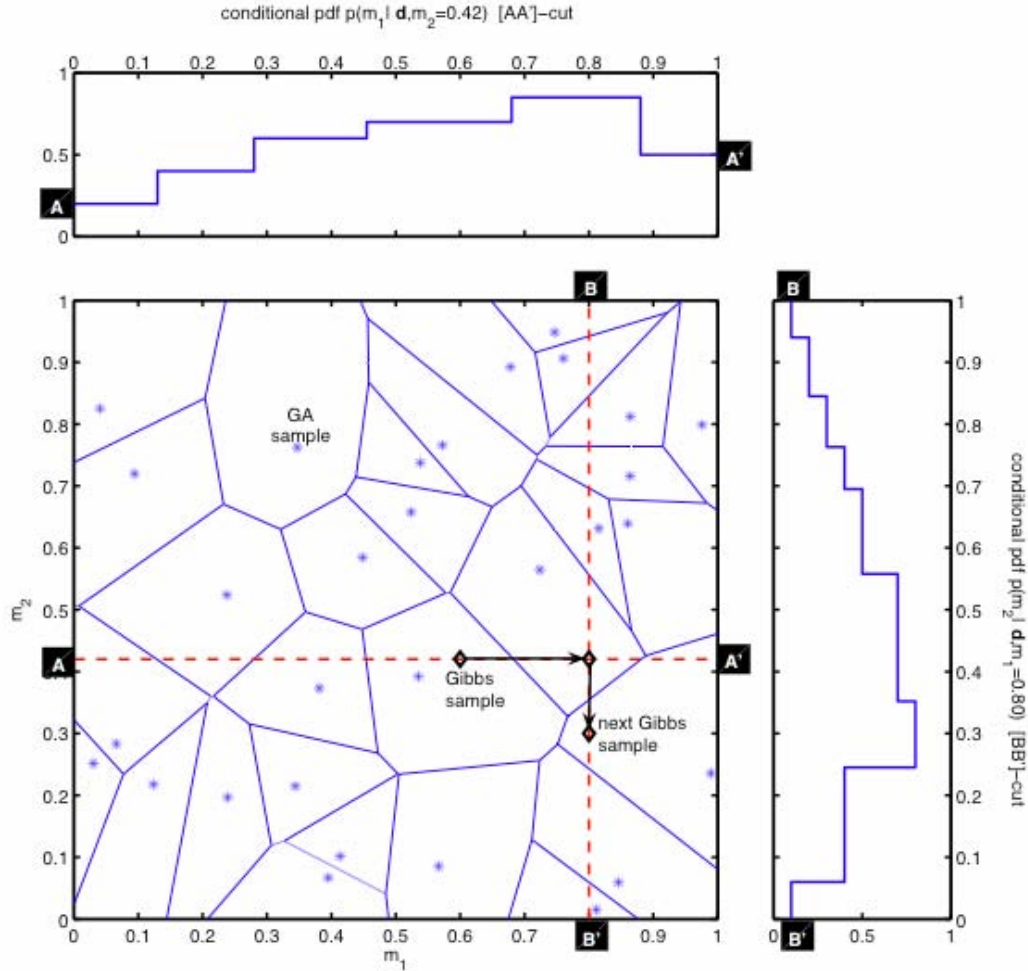


Figure 4 Voronoi cells for a simple 2-parameter search space and an approximate conditional 1-D density for a given cut. Dots represent GA points and squares represent the GS points sampling the approximate 2-D PPD.

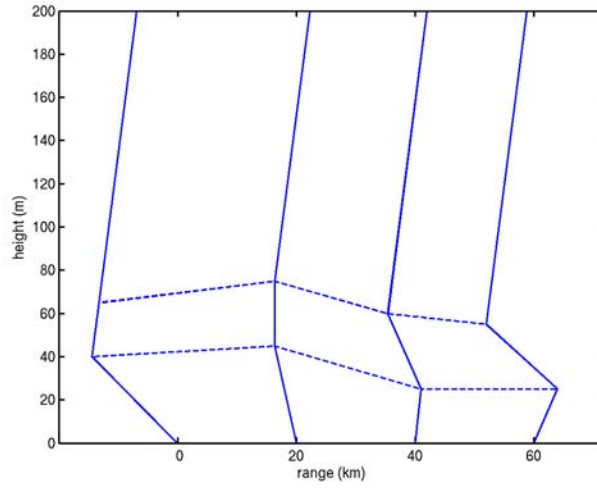


Figure 5 Range-dependent sixteen parameter M-profile with four parameters per 20 km. Vertical profile at any given range is calculated by linear interpolation of both the slopes and the layer thicknesses.

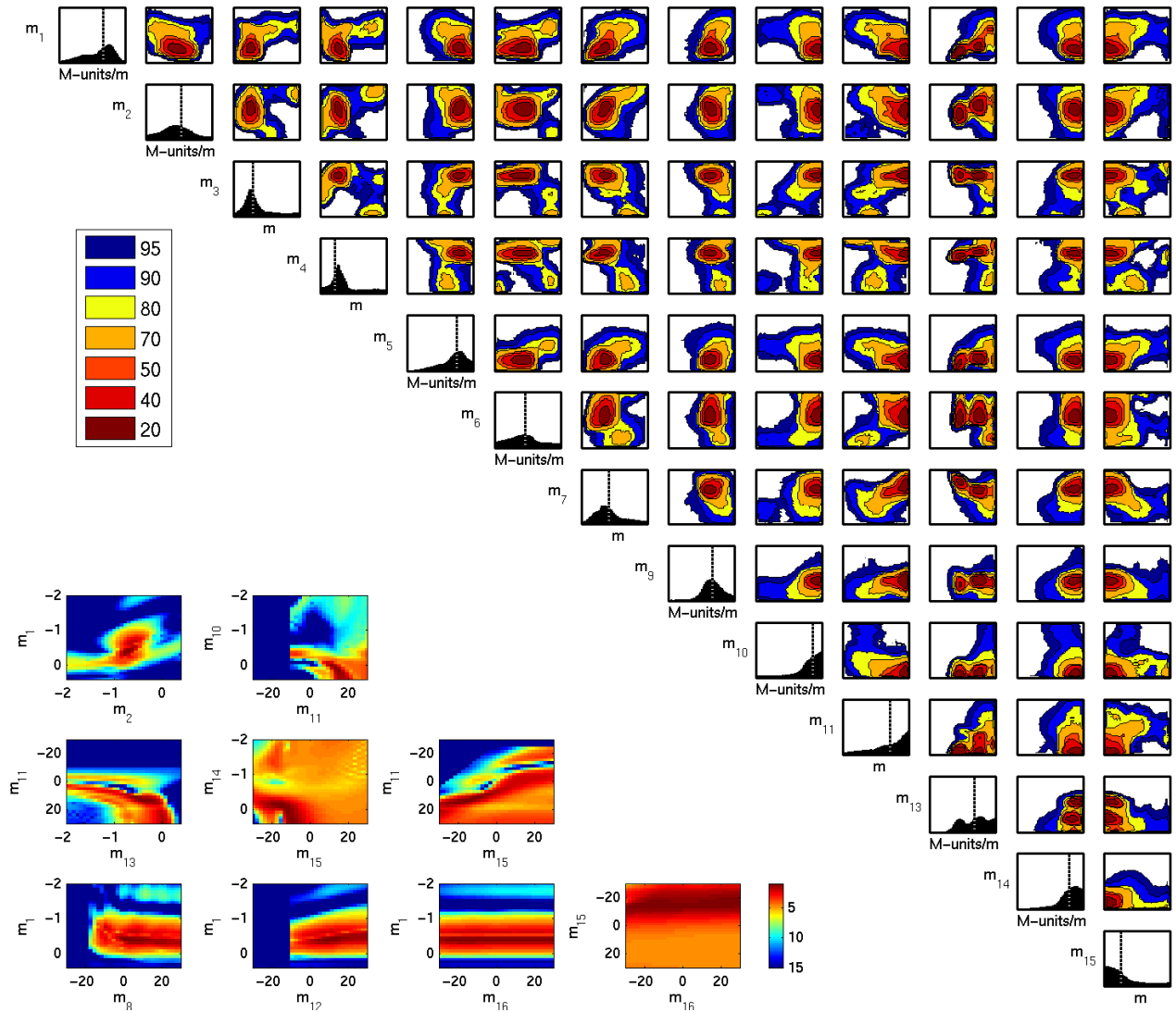


Figure 6: Marginal and conditional distributions. (a) 1-D (diagonal) and 2-D (upper diagonal) posterior probability distributions in terms of percent HPD, for the range-dependent SPANDAR data inversion. 13 parameters out of 16 are shown. Vertical lines in the 1-D plots show the GA MAP solution. (b) Normalized error function for various conditional planes. Each 2-D plot is obtained by fixing the other 14 parameters to their MAP values.

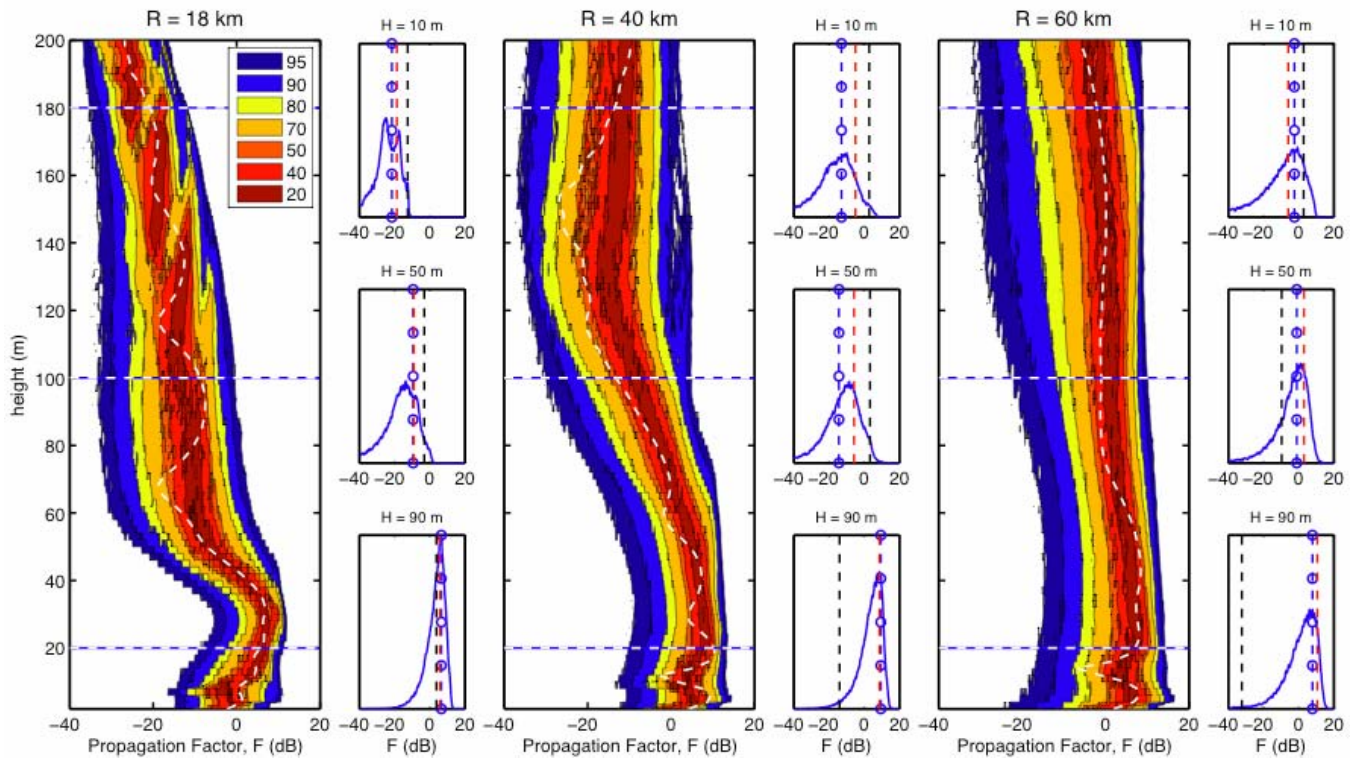


Figure 7 *Posterior probability densities for propagation factor F at three ranges: (a) 18, (b) 40, and (c) 60 km. Color plots show the PPD of F for height values between 0 m and 200 m in terms of percent HPD, with the MAP solution (dashed white). Horizontal lines represent the three altitudes analyzed in detail in the small plots shown next to the color plots at heights 180, 100, and 20 m, respectively from top to bottom. Vertical lines in the small plots represent the values of F at the corresponding height and range for the MAP solution (blue line with circles), helicopter measurement (red), and standard atmospheric assumption (black).*

IMPACT/APPLICATIONS

Knowledge of refractivity profiles is important for radar performance prediction. Using the radar clutter return to estimate refractivity gives a real-time estimate of the refractivity.

RELATED PROJECTS

Refractivity Data Fusion and Assimilation (Ted Rogers, SPAWAR): This project is concerned with near real-time techniques for inferring refractivity parameters from radar sea clutter.

REFERENCES

- [Gerstoft 03a] Gerstoft, P., L. Ted Rogers, W.S. Hodgkiss and J. Krolik Inversion for refractivity parameters from radar sea clutter, *Radio Science*, 38:1-22, (March 2003)
- [Gerstoft 03b] Gerstoft, P., L. T. Rodgers, W.S. Hodgkiss and L.J. Wagner, Refractivity estimation using multiple elevation angles, *IEEE Oceanic Eng.* (July 2003)

- [Gerstoft 04] P. Gerstoft, W.S. Hodgkiss, L.T. Rogers and M. Jablecki, Probability distribution of low altitude propagation loss from radar sea-clutter data, Radio Science, 39, doi:10.1029/2004/RS003077, Nov. 2004
- [Rogers, 2005] L.T. Rogers, M. Jablecki, and P Gerstoft, Posterior distribution of a statistic of propagation loss estimated from radar sea data, Radar Science, 2Vol. 40, No. 6, doi:10.1029/2004RS00311.
- [Sambridge, 1999] Malcolm Sambridge , Geophysical inversion with a neighbourhood algorithm—II. Appraising the ensemble, Geophysical Journal International, Vol 138 Page 727, doi:10.1046/j.1365-246x.1999.00900.x
- [Yardim 2005a] C. Yardim, P. Gerstoft, WS Hodgkiss, A fast hybrid genetic algorithm-Gibbs sampler approach to estimate geoacoustic parameter uncertainties, Underwater acoustic measurements, Crete 2005
- [Yardim 2005b] C. Yardim, P. Gerstoft, W. S. Hodgkiss, C.-F. Huang, Refractivity from Clutter (RFC) Estimation Using a Hybrid Genetic Algorithm - Markov Chain Monte Carlo Method, IEEE APS international and USNC/URSI National Radio Science meeting, 2005

PUBLICATIONS

- [Vasuvedan, 2006] S. Vasuvedan, R.H. Anderson, S Kraut, P. Gerstoft, L.T. Rogers, and J.L. Krolik, Recursive Bayesian electromagnetic refractivity estimation from Radar sea clutter, Radio Science, in press.
- [Yardim, 2006] C. Yardim, P. Gerstoft, and W.S. Hodgkiss, Estimation of radio refractivity from radar clutter using Bayesian Monte Carlo analysis, IEEE J Antenna and Propagation, 54, 1318-1327, doi:10.1109/TAP.2006.872673.
- [Yardim 2007] C. Yardim, P. Gerstoft, WS Hodgkiss, Statistical sea-borne duct estimation using a hybrid genetic algorithms -- Markov Chain Monte Carlo Method, submitted to Radar Science.